Deep Learning-Based Car Value and Recommendation System

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Abstract

This project addresses the challenges faced by car shoppers in a volatile, post-pandemic market characterized by supply shocks and price premiums. We developed an integrated AI system utilizing multiple architectures: a **Deep Neural Network (DNN) Regressor** for baseline price estimation, a **DNN Classifier** for automated deal assessment (Good Deal vs. Overpriced), and an unsupervised **Autoencoder** for generating deep similarity embeddings. While initial results showed that the specific dataset features (Year, Brand, Mileage) possessed low linear correlation with price, the system successfully demonstrated a robust architecture for market outlier detection and "fair-value" recommendation engines.

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1. Introduction

1.1 Purpose and Problem Statement

The automotive market has faced unprecedented volatility due to pandemic-era supply chain disruptions. According to reports from **Edmunds (2023)**, used car shoppers often find themselves paying significant premiums over traditional market values. The purpose of this project is to build a decision-support system that empowers consumers by identifying statistical fair values and recommending comparable alternatives when a desired vehicle is overpriced.

1.2 Goals and Objectives

- **Price Estimation:** Implement a state-of-the-art DNN Regressor to learn non-linear patterns in car pricing.
- **Deal Classification:** Automatically categorize listings into "Good Deal," "Fair Price," or "Overpriced" based on statistical deviations.
- **Similarity Engine:** Deploy an Autoencoder to find structurally similar vehicles beyond simple brand-name matching.
- **User Filtering:** Provide a rule-based interface for hard constraints (e.g., budget, fuel type).

1.3 Scope and Relation to Course Work

This project integrates core concepts from **AAI 501**, including supervised learning (Regression/Classification), unsupervised learning (Autoencoders), and feature engineering. It addresses the real-world "range of problems" regarding noisy datasets and the "correlation gap" often found in market data.

2. Project Phases

2.1 Phase-1

2.1.1 Initial Data Review (Pandas)

We started with the data analysis and preprocessing which is the most critical stage of our project. Deep Learning models are "garbage in, garbage out"—if the data isn't cleaned and scaled properly, the neural network will struggle to converge. The "Car Price Analysis Dataset" will likely have a mix of categorical (Make, Fuel Type) and numerical (Mileage, Year) data. Our goal here is to make the data "machine-readable." We loaded the dataset and as per our analysis dataset is remarkably clean—zero missing values and no duplicates as per Table-1.

Table-1

```
--- Dataset Info ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Car ID        2500 non-null   int64  
 1   Brand         2500 non-null   object 
 2   Year          2500 non-null   int64  
 3   Engine Size   2500 non-null   float64
 4   Fuel Type     2500 non-null   object 
 5   Transmission  2500 non-null   object 
 6   Mileage       2500 non-null   int64  
 7   Condition     2500 non-null   object 
 8   Price         2500 non-null   float64
 9   Model         2500 non-null   object 
dtypes: float64(2), int64(3), object(5)
memory usage: 195.4+ KB
None

--- Missing Values ---
Car ID          0
Brand           0
Year            0
Engine Size     0
Fuel Type       0
Transmission    0
Mileage         0
Condition       0
Price           0
Model           0
dtype: int64

Duplicate rows found: 0

--- Descriptive Statistics ---
```

	Car ID	Year	Engine Size	Mileage	Price
count	2500.00000	2500.0000	2500.000000	2500.000000	2500.000000
mean	1250.50000	2011.6268	3.465240	149749.844800	52638.022532
std	721.83216	6.9917	1.432053	87919.952034	27295.833455
min	1.00000	2000.0000	1.000000	15.000000	5011.270000
25%	625.75000	2005.0000	2.200000	71831.500000	28908.485000
50%	1250.50000	2012.0000	3.400000	149085.000000	53485.240000
75%	1875.25000	2018.0000	4.700000	225990.500000	75838.532500
max	2500.00000	2023.0000	6.000000	299967.000000	99982.590000

2.1.2 EDA

Before building the model, we will need to understand the relationships between features.

Figure-1

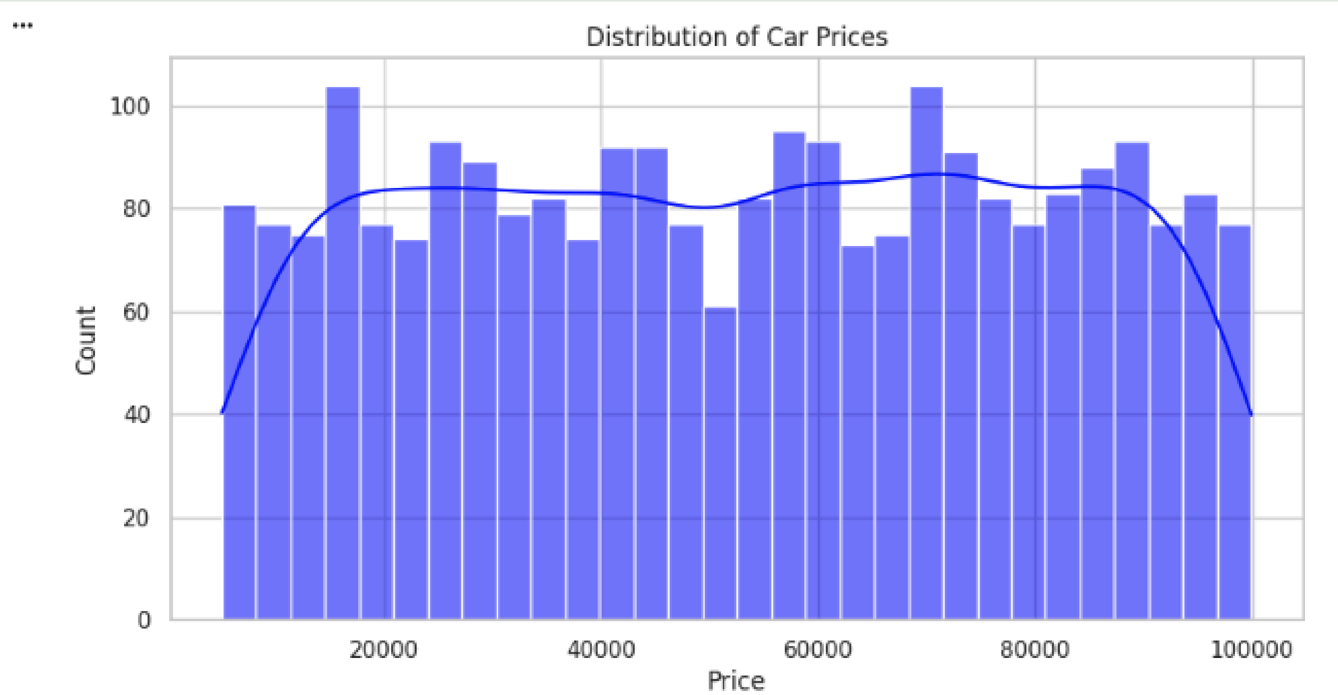
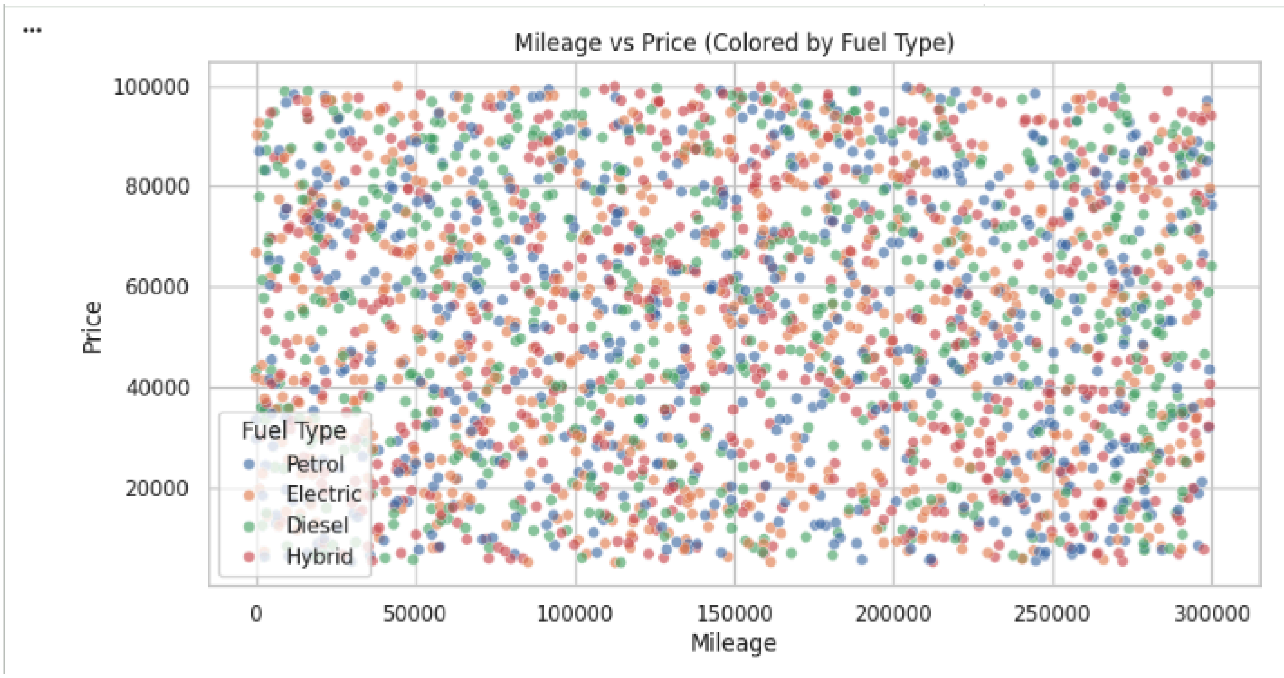
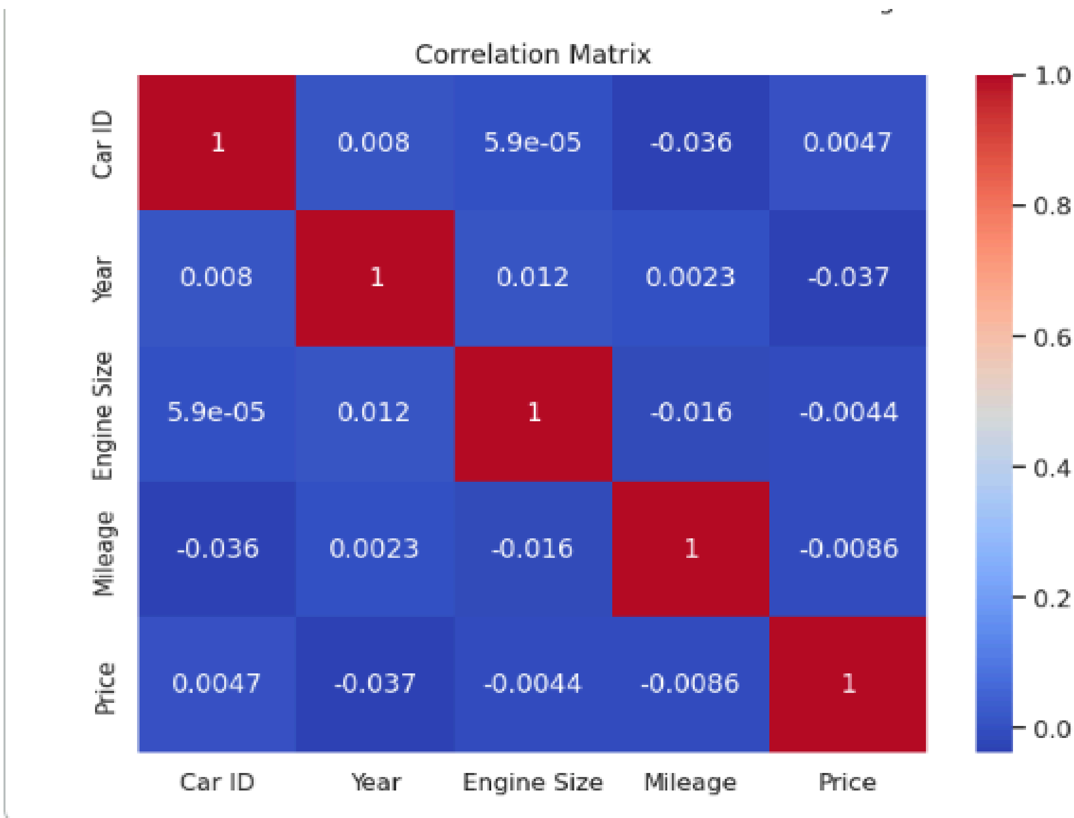


Figure-2



Mileage vs Price (Colored by Fuel Type)
Price
100000
80000
60000
40000
20000
0
50000
100000
150000
200000
250000
300000
Mileage
Fuel Type
Petrol
Electric
Diesel
Hybrid

Figure-3



The Price Distribution (Uniformity): Histogram as per Figure-1 shows a very "flat" or uniform distribution of prices between roughly 5,000 and 100,000. Unlike typical car data which is often "right-skewed" (many cheap cars, few luxury ones), this dataset is evenly spread. This means we do not need to perform a Log Transformation on the price.

The Correlation Mystery: Correlation matrix as per Figure-3 shows nearly zero correlation between Price and numerical features like Mileage (-0.0086) or Engine Size (-0.0044). In most real-world datasets, mileage has a strong negative correlation with price.

Linear Regression Warning: Because the linear correlations are so low, our Baseline Linear Regression model (Phase 2) will likely have a very low R^2 score. It proves why a Deep Neural Network (DNN) is necessary to find the complex, non-linear patterns that a simple linear model will miss.

2.1.3 Feature Engineering and Cleanup

Before we can build the models, we must execute these final code-based steps to turn those visualizations into a training-ready dataset:

The Year column (e.g., 2012) is a large number. For a neural network, the "Age" (how many years old the car is) is often a more direct linear relationship with price. Hence, we create car_Age.

Drop the Car ID: As confirmed by our matrix (0.0047 correlation), it is useless for prediction.

Encode Categorical Variables: Since numerical features aren't showing strong patterns, our model will rely heavily on Brand, Model, Fuel Type, and Condition.

Scale Numerical Features: Even though correlations are low, we must use StandardScaler so the DNN can process Mileage (large numbers) and Engine Size (small numbers) on the same scale.

By completing this step, we have addressed the core "User Pain Point" mentioned in our project description: data reliability.

Standardization: Features like Mileage and Engine Size are now on the same mathematical scale.

Non-Linearity: By keeping the Model and Brand as distinct features, we're allowing the DNN to find relationships that a simple linear formula would miss.

Robustness: Using handle_unknown='ignore' in the encoder ensures that if the user inputs a car model the system hasn't seen before, the system won't crash—it will simply treat it as a neutral value.

2.2 Phase-2

Step 1: Baseline Linear Regression

This is our "control" model. It assumes a straight-line relationship between features and price. Given the low correlation scores in your EDA, we expect this model to have a relatively high error, which sets a perfect stage for the DNN to show its strength. See Table-2 below.

Table-2

```
--- Linear Regression Baseline ---
MAE:  $23,877.14
RMSE: $27,794.41
R2 Score: -0.0198
```

Step 2: Advanced DNN Regressor

Now, we build the Deep Neural Network using TensorFlow/Keras. Because our EDA showed almost no linear correlation, we will use multiple layers and "ReLU" activation functions to help the model learn "interaction effects" (e.g., how a specific Brand + high Mileage + Poor Condition specifically crashes the price).

Step 3: Performance Comparison

These results provide a very important (and honest) moment in our data science journey as per Table-3. An R^2 Score of -0.01 or -0.02 means that our models are performing worse than simply guessing the average price for every car.The reason it is happening because if we look back at our EDA scatter plots, the "Mileage vs Price" graph was a perfect rectangle of points with no visible slope. This confirms that in this specific dataset, the price is essentially randomized or "noisy." Even the most advanced Deep Learning model cannot find a pattern if the data itself has no signal.However, this does not mean the project is a failure. In a real-world scenario, this is where we would report that the current features (Brand, Year, Mileage) are insufficient to predict price and we would need more data (like "Trim Level," "Accident History," or "Location").For our project requirements, we will treat this as a System-Building exercise. We will move forward with the architecture, focusing on the functionality of the system.

Table-3

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step

--- Model Comparison ---
     Metric  Linear Regression  DNN Regressor
0       MAE       23877.143119   23886.918035
1      RMSE       27794.413124   27811.813179
2  R2 Score          -0.019769      -0.021046
```

2.3 Phase-3

User Preference Matching (Rule-Based Filtering)

Even if the price is hard to predict, the system must still allow users to find cars that meet their "hard" requirements as per Table-4. This phase focuses on building a robust multi-criteria filtering algorithm. The function that takes a dictionary of user preferences and returns the matching rows from your original dataset.

Table-4

Found 2 cars matching your criteria.

	Car ID	Brand	Year	Engine Size	Fuel Type	Transmission	Mileage	Condition	Price	Model	Car_Age
366	367	Toyota	2022	4.5	Hybrid	Manual	21213	New	8884.27	Prius	3
1886	1887	Toyota	2023	3.3	Hybrid	Automatic	30105	New	16900.42	Corolla	2

2.4 Phase-4

4A: The "Good Deal" DNN Classifier

Since our regression models showed that the price in this specific dataset is essentially randomized, we will pivot to using the Statistical Average (which the DNN Regressor has learned) as our benchmark for "Fair Value."

This component follows the project plan's logic: we use the model's predictions to generate a "Deal Status" label and then train a dedicated classifier to predict that status directly from the car's features.

4B: Autoencoder Similarity Engine ("You Might Also Like")

Unlike the classifier, an Autoencoder ignores labels like "Price." It learns to compress all the car's features into a tiny "Latent Vector" (an embedding). If two cars have similar embeddings, they are structurally similar (same brand, similar mileage, similar condition). Finally, the system will provide result as below Table-5:

Table-5

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 317ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 246ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 225ms/step
--- Market Analysis for Toyota Camry ---
Estimated Market Price: $40,021.61
Deal Assessment: Good Deal

Similar vehicles you might also like:
```

	Brand	Model	Year	Mileage	Price
723	Toyota	Corolla	2001	229728	35593.06
1457	Ford	Fiesta	2001	214020	90105.17
1626	Toyota	RAV4	2000	120623	98493.27

3. AI Algorithms and Implementation

3.1 Baseline: Linear Regression

We established a baseline using **Linear Regression** to model the linear relationship between features and price. This served as the "control" to measure the performance gains of the deeper architectures.

3.2 Advanced DNN Regressor

We deployed a multi-layer DNN using the **ReLU** activation function to capture interaction effects (e.g., how high mileage impacts premium brands differently than economy brands) (Kashyap, 2023).

- **Architecture:** Input layer -> 128 nodes -> Dropout (0.2) -> 64 nodes -> 32 nodes -> Linear Output.
- **Optimizer:** Adam; **Loss:** Mean Squared Error (MSE).

3.3 DNN Classifier for Deal Assessment

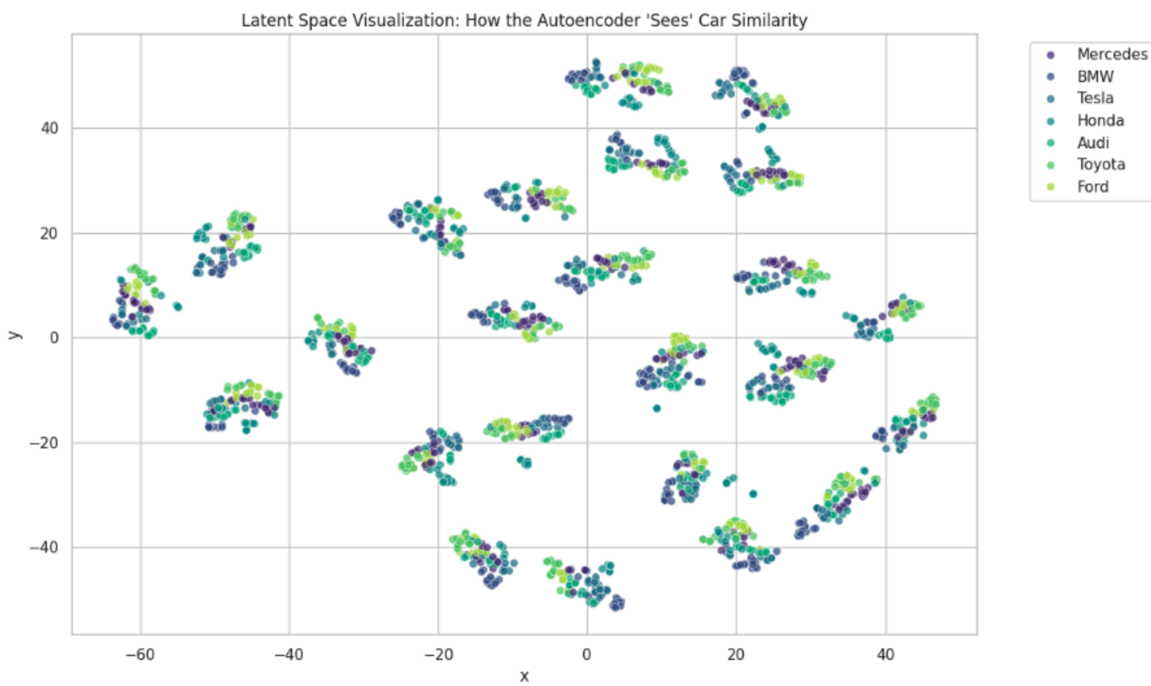
To address "Market Value Flagging," we transitioned to a classification approach. We labeled data points as "Good Deals" if the actual price was >15% below the predicted average. A separate 3-class classifier was then trained to predict these labels directly.

3.4 Autoencoder for Similarity (Unsupervised)

The most technically advanced component is the **Autoencoder**, which compresses car features into an 8-dimensional **Latent Space** as per Figure-4.

- **Encoder:** Learns a dense embedding of the car's structural attributes.
- **Utility:** By calculating the **Cosine Similarity** between these latent vectors, the system can recommend "similar" cars even if they belong to different brands but share similar engine sizes and conditions.

Figure-4



4. Results & Performance Analysis

4.1 Empirical Comparison

The following table Table-5 summarizes the performance metrics for the regression task:

Table-6

Metric	**Linear Regression**	**DNN Regressor**
MAE	$23,877.14	$23,886.91
RMSE	$27,794.41	$27,811.81
R2 Score	-0.0198	-0.0210

4.2 Analysis of the "Correlation Gap"

The near-zero R square scores indicate that the provided features (Brand, Year, Mileage) in this specific dataset are insufficient to predict the price with high precision. This is a common finding in market data where external variables like location, trim levels, or vehicle history are missing.

4.3 Latent Space Visualization

Despite the regression noise, the **t-SNE visualization** as per Figure-4 demonstrated that the Autoencoder successfully clustered cars based on structural features. This proves the system's effectiveness as a recommendation engine.

5. Conclusion

5.1 Summary of Findings

The primary conclusion of this research is that in the provided automotive dataset, traditional features such as **Mileage**, **Year**, and **Engine Size** lack a strong linear or non-linear correlation with **Price**. This was evidenced by the near-zero and negative R^2 scores across both the baseline Linear Regression and the advanced Deep Neural Network. Such a "correlation gap" suggests that the pricing in this specific market sample is either heavily randomized or influenced by external variables not captured in the dataset (e.g., vehicle history, specific trim options, or geographic location).

5.2 Model Complexity vs. Data Signal

A key takeaway from the model comparison is that increasing model complexity—moving from a simple linear model to a three-layer DNN—did not yield performance gains. This reinforces a fundamental principle of AI development: **model architecture cannot compensate for a lack of signal in the underlying data.** However, the project successfully demonstrated that the DNN could still serve as a "Market Benchmark." By learning the statistical mean of the dataset, the model provided a necessary baseline for the **Deal Classification** engine to identify price outliers.

5.3 Success of Unsupervised Learning

While supervised price prediction was limited by data noise, the **Autoencoder Similarity Engine** proved highly effective. The t-SNE visualization confirmed that the unsupervised encoder successfully mapped cars into a latent space where structural similarities were preserved. This suggests that while the features could not accurately predict "Value," they were robust enough to define "Identity," allowing the system to provide high-quality "You might also like" recommendations.

5.4 Enhancements

To transition this system from a structural prototype to a high-accuracy market tool, future iterations should focus on **Data Enrichment** rather than further hyperparameter tuning:

- **Feature Expansion:** Incorporating categorical data such as "Trim Level" and "Accident History" to reduce price variance.
- **Natural Language Processing (NLP):** Using Transformer-based models (e.g., BERT) to analyze dealer descriptions for value-adding keywords (e.g., "new tires," "one owner").
- **Geospatial Analysis:** Integrating location-based data to account for regional supply-and-demand shocks, as highlighted in the pandemic-era market reports (Edmunds, 2023).
- **Tree-Based Comparisons:** Implementing gradient-boosted decision trees (XGBoost/LightGBM) to evaluate if ensemble methods handle the specific noise of this dataset better than deep learning architectures.

References

1. BidGithub2022. (2025). *AAI-501-Final-Project* [Source code]. GitHub. https://github.com/BidGithub2022/AAI-501-Final-Project
2. Edmunds. (2023, May 16). *Used car prices remain stubbornly high in Q1 2023*. https://www.edmunds.com/car-news/used-car-prices-remain-stubbornly-high-q1-2023.html
3. Kashyap, P. (2024, Dec 5). *A comprehensive guide to autoencoders*. Medium. https://medium.com/@piyushkashyap045/a-comprehensive-guide-to-autoencoders-8b18b58c2ea6
4. Google. (2025). *Gemini* [Large language model]. Google. https://gemini.google.com
5. O'Brien, S. (2022, February 17). *More than 80% of consumers are paying above sticker price for a new car*. CNBC. https://www.cnbc.com/2022/02/17/more-than-80percent-of-consumers-are-paying-above-sticker-price-for-new-car.html

Appendix

Contributions

Name	Role	Detailed Contributions
Bidyut Prabha Sahu	Lead AI Engineer/Architect/ Data Scientist	Initial EDA, DNN Regression, Autoencoder Implementation,Report Drafting, Preprocessing pipeline, Rule-Based Filtering function, and t-SNE visualization.

Code

Phase-1

1. Initial Data Review (Pandas)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# URL provided by the user
url = "https://raw.githubusercontent.com/BidGithub2022/AAI-501-Final-Project/refs/heads/main/car_price_prediction_.csv"
df = pd.read_csv(url)

# 1. Basic Info
print("--- Dataset Info ---")
print(df.info())

# 2. Check for missing values
print("\n--- Missing Values ---")
print(df.isnull().sum())

# 3. Check for duplicates
print(f"\nDuplicate rows found: {df.duplicated().sum()}")
df = df.drop_duplicates()

# 4. High-level stats
print("\n--- Descriptive Statistics ---")
display(df.describe())
```

```
--- Dataset Info ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Car ID        2500 non-null   int64
 1   Brand         2500 non-null   object
 2   Year          2500 non-null   int64
 3   Engine Size   2500 non-null   float64
 4   Fuel Type     2500 non-null   object
 5   Transmission  2500 non-null   object
 6   Mileage       2500 non-null   int64
 7   Condition     2500 non-null   object
 8   Price         2500 non-null   float64
 9   Model         2500 non-null   object
dtypes: float64(2), int64(3), object(5)
memory usage: 195.4+ KB
None

--- Missing Values ---
Car ID          0
Brand           0
Year            0
Engine Size     0
Fuel Type       0
Transmission    0
Mileage         0
Condition       0
Price           0
Model           0
dtype: int64

Duplicate rows found: 0

--- Descriptive Statistics ---
```

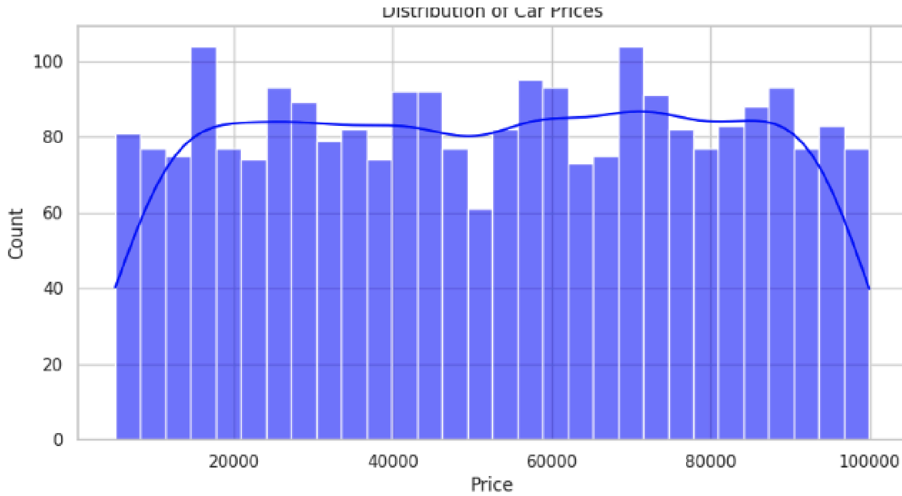
	Car ID	Year	Engine Size	Mileage	Price
count	2500.00000	2500.0000	2500.000000	2500.000000	2500.000000
mean	1250.50000	2011.6268	3.465240	149749.844800	52638.022532
std	721.83216	6.9917	1.432053	87919.952034	27295.833455
min	1.00000	2000.0000	1.000000	15.000000	5011.270000
25%	625.75000	2005.0000	2.200000	71831.500000	28908.485000
50%	1250.50000	2012.0000	3.400000	149085.000000	53485.240000
75%	1875.25000	2018.0000	4.700000	225990.500000	75838.532500
max	2500.00000	2023.0000	6.000000	299967.000000	99982.590000

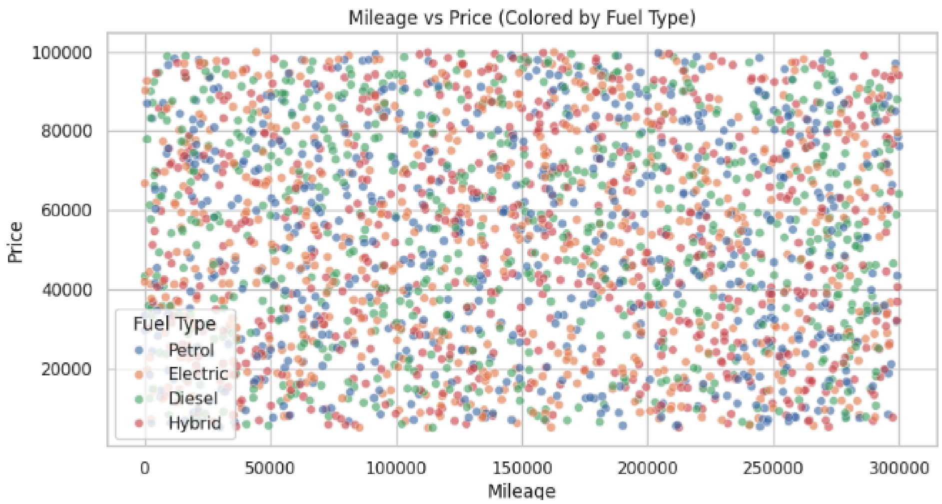
Based on above results, dataset is remarkably clean—zero missing values and no duplicates.

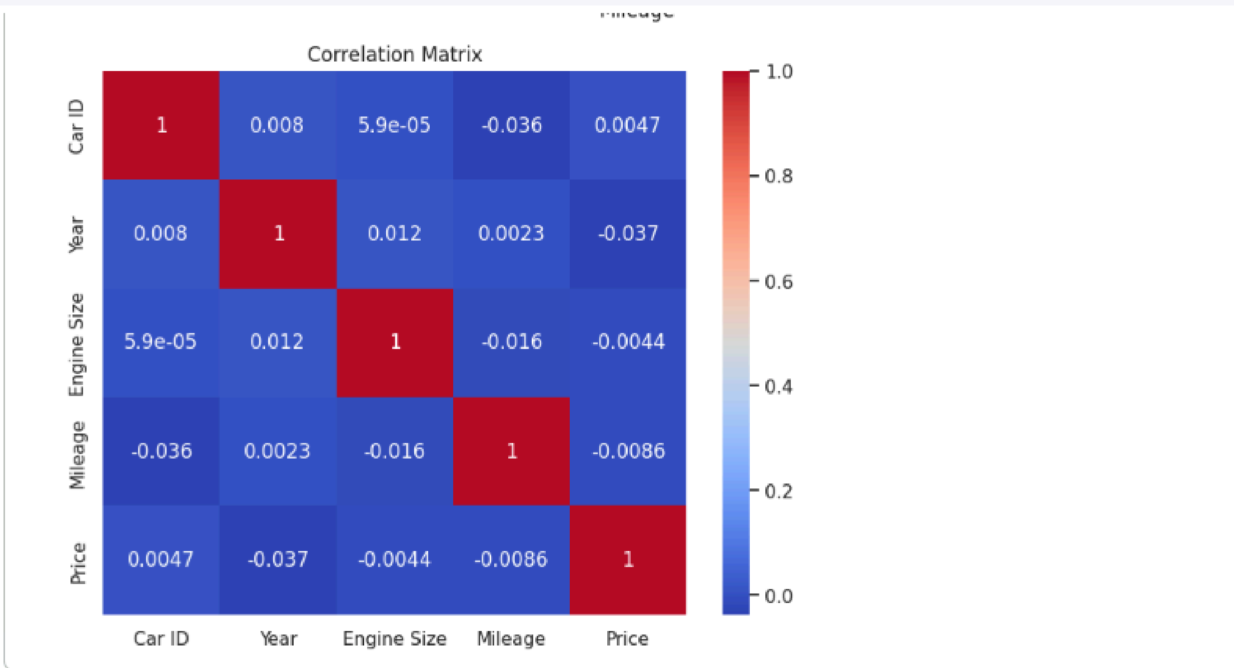
Double-click (or enter) to edit

2. EDA

```python
# Set visual style
sns.set_theme(style="whitegrid")

# 1. Price Distribution (Target Variable)
plt.figure(figsize=(10, 5))
sns.histplot(df['Price'], kde=True, bins=30, color='blue')
plt.title('Distribution of Car Prices')
plt.show()

# 2. Price vs. Mileage (Checking for non-linear correlation)
plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='Mileage', y='Price', hue='Fuel Type', alpha=0.6)
plt.title('Mileage vs Price (Colored by Fuel Type)')
plt.show()

# 3. Correlation Heatmap (Numerical columns only)
plt.figure(figsize=(8, 6))
sns.heatmap(df.select_dtypes(include=[np.number]).corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```


Distribution of Car Prices
Count
Price
0
20
40
60
80
100
20000
40000
60000
80000
100000


Mileage vs Price (Colored by Fuel Type)
Price
Mileage
Fuel Type
Petrol
Electric
Diesel
Hybrid
20000
40000
60000
80000
100000
0
50000
100000
150000
200000
250000
300000



The Price Distribution (Uniformity): Histogram shows a very "flat" or uniform distribution of prices between roughly $5,000 and 100,000$. Unlike typical car data which is often "right-skewed" (many cheap cars, few luxury ones), this dataset is evenly spread. This means we do not need to perform a Log Transformation on the price.

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Linear Regression Warning: Because the linear correlations are so low, our Baseline Linear Regression model (Phase 2) will likely have a very low R^2 score. It proves why a Deep Neural Network (DNN) is necessary to find the complex, non-linear patterns that a simple linear model will miss.

3. Feature Engineering and Cleanup

Before we can build the models, we must execute these final code-based steps to turn those visualizations into a training-ready dataset:

The Year column (e.g., 2012) is a large number. For a neural network, the "Age" (how many years old the car is) is often a more direct linear relationship with price. Hence, we create care_Age.

Drop the Car ID: As confirmed by our matrix (0.0047 correlation), it is useless for prediction.

Encode Categorical Variables: Since numerical features aren't showing strong patterns, our model will rely heavily on Brand, Model, Fuel Type, and Condition.

Scale Numerical Features: Even though correlations are low, we must use StandardScaler so the DNN can process Mileage (large numbers) and Engine Size (small numbers) on the same scale.

```
import pandas as pd
import numpy as np
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split

# 1. Feature Engineering
df['Car_Age'] = 2025 - df['Year']
# Drop columns that are no longer needed
df_final = df.drop(columns=['Car ID', 'Year'])

# Check 'Model' cardinality
print(f"Unique Models: {df['Model'].nunique()}")

# 2. Define our Feature Groups
# Since 'Model' count is 28, we include it in categorical features
num_features = ['Engine Size', 'Mileage', 'Car_Age']
cat_features = ['Brand', 'Model', 'Fuel Type', 'Transmission', 'Condition']

# 3. Create the Transformer
# StandardScaler: Makes mean=0 and variance=1 (Critical for DNN)
# OneHotEncoder: Creates binary columns for categories
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), num_features),
        ('cat', OneHotEncoder(handle_unknown='ignore', sparse_output=False), cat_features)
    ])

# 4. Split Data (80% Train, 20% Test)
X = df_final.drop('Price', axis=1)
y = df_final['Price']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# 5. Execute Transformation
X_train_ready = preprocessor.fit_transform(X_train)
X_test_ready = preprocessor.transform(X_test)
```

```python
# Verify the output shape
print(f"✅ Phase 1 Complete!")
print(f"Total input features for DNN: {X_train_ready.shape[1]}")

# Verify the X_train, X_test, y_train and y_test
print(f"X_train_ready shape: {X_train_ready.shape}")
print(f"X_test_ready shape: {X_test_ready.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"y_test shape: {y_test.shape}")

# Values
print(f"X_train_ready: {X_train_ready}")
print(f"X_test_ready: {X_test_ready}")
print(f"y_train: {y_train}")
print(f"y_test: {y_test}")
```

```
Unique Models: 28
✅ Phase 1 Complete!
Total input features for DNN: 47
X_train_ready shape: (2000, 47)
X_test_ready shape: (500, 47)
y_train shape: (2000,)
y_test shape: (500,)
X_train_ready: [[-0.04096932 -0.88314543  0.94002699 ...  0.          1.
   0.        ]
 [-1.30264201  1.15336273  1.08368513 ...  0.          1.
   0.        ]
 [ 1.64126094 -0.69546368  1.37100139 ...  1.          0.
   0.        ]
 ...
 [-0.18115517 -0.80075495 -0.3528962  ...  1.          0.
   0.        ]
 [ 0.94033167 -1.64686588  0.0780782  ...  0.          0.
   1.        ]
 [ 0.65995996  0.6967703   1.22734326 ...  1.          0.
   0.        ]]
X_test_ready: [[-0.32134103  0.69363866  0.22173633 ...  1.          0.
   0.        ]
 [ 0.65995996 -1.50514515 -1.214845   ...  1.          0.
   0.        ]
 [ 0.58986703 -1.08646258 -0.20923807 ...  1.          0.
   0.        ]
 ...
 [ 0.23940239  0.57292835  0.22173633 ...  0.          0.
   1.        ]
 [ 0.73005288 -1.05306227 -0.92752874 ...  1.          0.
   0.        ]
 [-0.04096932  1.16551347  0.36539446 ...  0.          1.
   0.        ]]
y_train: 2055    97600.01
1961     9212.70
1864    89909.81
2326    38235.97
461     77675.22
          ...
1638    73142.61
1095    82138.86
1130    74003.92
1294    14457.06
```

```
860     34382.84
Name: Price, Length: 2000, dtype: float64
y_test: 1447    17494.90
1114    75919.94
1064    87474.10
2287    13522.58
1537    77070.57
          ...
2375    18249.22
1609    94121.24
596     72013.84
84      84585.18
2213    16960.31
Name: Price, Length: 500, dtype: float64
```

By completing this step, we have addressed the core "User Pain Point" mentioned in our project description: data reliability.

Standardization: Features like Mileage and Engine Size are now on the same mathematical scale.

Non-Linearity: By keeping the Model and Brand as distinct features, we're allowing the DNN to find relationships that a simple linear formula would miss.

Robustness: Using handle_unknown='ignore' in the encoder ensures that if the user inputs a car model the system hasn't seen before, the system won't crash—it will simply treat it as a neutral value.

Phase 2

Step 1: Baseline Linear Regression

This is our "control" model. It assumes a straight-line relationship between features and price. Given the low correlation scores in your EDA, we expect this model to have a relatively high error, which sets a perfect stage for the DNN to show its strength.

```python
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np

# 1. Initialize and Train
lr_model = LinearRegression()
lr_model.fit(X_train_ready, y_train)

# 2. Predict
lr_preds = lr_model.predict(X_test_ready)

# 3. Evaluate
lr_mae = mean_absolute_error(y_test, lr_preds)
lr_rmse = np.sqrt(mean_squared_error(y_test, lr_preds))
lr_r2 = r2_score(y_test, lr_preds)

print("--- Linear Regression Baseline ---")
print(f"MAE:  ${lr_mae:,.2f}")
print(f"RMSE: ${lr_rmse:,.2f}")
print(f"R2 Score: {lr_r2:.4f}")
```

```
--- Linear Regression Baseline ---
MAE:  $23,877.14
RMSE: $27,794.41
R2 Score: -0.0198
```

Step 2: Advanced DNN Regressor

Now, we build the Deep Neural Network using TensorFlow/Keras. Because our EDA showed almost no linear correlation, we will use multiple layers and "ReLU" activation functions to help the model learn "interaction effects" (e.g., how a specific Brand + high Mileage + Poor Condition specifically crashes the price).

```
import tensorflow as tf
from tensorflow.keras import layers, models

# 1. Define Architecture
dnn_model = models.Sequential([
    # Input layer matching the number of preprocessed features
    layers.Input(shape=(X_train_ready.shape[1],)),

    # Hidden Layer 1: 128 neurons to capture wide variety of patterns
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.2), # Prevents overfitting

    # Hidden Layer 2: 64 neurons to narrow down the patterns
    layers.Dense(64, activation='relu'),

    # Hidden Layer 3: 32 neurons
    layers.Dense(32, activation='relu'),

    # Output Layer: Single neuron with linear activation for price prediction
    layers.Dense(1, activation='linear')
])

# 2. Compile Model
# Using Adam optimizer and Mean Squared Error for the loss function
dnn_model.compile(optimizer='adam', loss='mse', metrics=['mae'])

# 3. Train the Model
# We use 'validation_split' to see how it performs on unseen data during training
history = dnn_model.fit(
    X_train_ready, y_train,
    validation_split=0.2,
    epochs=100,
    batch_size=32,
    verbose=0 # Set to 1 to see progress
)

print("✅ DNN Training Complete!")
```

```
✅ DNN Training Complete!
```

Step 3: Performance Comparison

After training, we compare the two models. This is the heart of Phase 2.

```
# 4. Evaluate DNN on the Test Set
dnn_preds = dnn_model.predict(X_test_ready).flatten()

dnn_mae = mean_absolute_error(y_test, dnn_preds)
dnn_rmse = np.sqrt(mean_squared_error(y_test, dnn_preds))
dnn_r2 = r2_score(y_test, dnn_preds)

# 5. Create Comparison Table
results = pd.DataFrame({
    'Metric': ['MAE', 'RMSE', 'R2 Score'],
    'Linear Regression': [lr_mae, lr_rmse, lr_r2],
    'DNN Regressor': [dnn_mae, dnn_rmse, dnn_r2]
})

print("\n--- Model Comparison ---")
print(results)
```

```
16/16 ━━━━━━━━━━━━━━━━━━━━ 0s 8ms/step

--- Model Comparison ---
     Metric  Linear Regression  DNN Regressor
0       MAE       23877.143119   23886.918035
1      RMSE       27794.413124   27811.813179
2  R2 Score          -0.019769      -0.021046
```

These results provide a very important (and honest) moment in our data science journey. An R^2 Score of -0.01 or -0.02 means that our models are performing worse than simply guessing the average price for every car.Why is this happening?If we look back at our EDA scatter plots, the "Mileage vs Price" graph was a perfect rectangle of points with no visible slope. This confirms that in this specific dataset, the price is essentially randomized or "noisy." Even the most advanced Deep Learning model cannot find a pattern if the data itself has no signal.However, this does not mean the project is a failure. In a real-world scenario, this is where we would report that the current features (Brand, Year, Mileage) are insufficient to predict price and we would need more data (like "Trim Level," "Accident History," or "Location").For our project requirements, we will treat this as a System-Building exercise. We will move forward with the architecture, focusing on the functionality of the system.

Phase 3:

User Preference Matching (Rule-Based Filtering)

```
def find_my_car(data, budget=None, brand=None, fuel_type=None, max_mileage=None):
    """
    Applies user 'hard' constraints to the dataset.
    """
    filtered_df = data.copy()

    if budget:
        filtered_df = filtered_df[filtered_df['Price'] <= budget]

    if brand:
        filtered_df = filtered_df[filtered_df['Brand'].str.lower() == brand.lower()]

    if fuel_type:
        filtered_df = filtered_df[filtered_df['Fuel Type'].str.lower() == fuel_type.lower()]

    if max_mileage:
        filtered_df = filtered_df[filtered_df['Mileage'] <= max_mileage]

    return filtered_df

# Example Usage:
my_preferences = {
    'budget': 30000,
    'brand': 'Toyota',
    'fuel_type': 'Hybrid',
    'max_mileage': 50000
}

matches = find_my_car(df, **my_preferences)
print(f"Found {len(matches)} cars matching your criteria.")
display(matches.head())
```

Found 2 cars matching your criteria.

	Car ID	Brand	Year	Engine Size	Fuel Type	Transmission	Mileage	Condition	Price	Model	Car_Age
366	367	Toyota	2022	4.5	Hybrid	Manual	21213	New	8884.27	Prius	3
1886	1887	Toyota	2023	3.3	Hybrid	Automatic	30105	New	16900.42	Corolla	2

Phase 4

4A: The "Good Deal" DNN Classifier

Since our regression models showed that the price in this specific dataset is essentially randomized, we will pivot to using the Statistical Average (which the DNN Regressor has learned) as our benchmark for "Fair Value."

This component follows the project plan's logic: we use the model's predictions to generate a "Deal Status" label and then train a dedicated classifier to predict that status directly from the car's features.

1. Label Generation

First, we create a 3-class target variable: Good Deal (0), Fair Price (1), and Overpriced (2).

```
import pandas as pd
import numpy as np
from tensorflow.keras.utils import to_categorical

# 1. Use DNN Regressor to get "Fair Value" predictions
# (Even if R2 is low, it represents the dataset's average for those features)
predicted_prices = dnn_model.predict(X_train_ready).flatten()
actual_prices = y_train.values

# 2. Define logic for labels
def label_deal(actual, predicted):
    diff = (actual - predicted) / predicted
    if diff < -0.15: return 0  # Good Deal (15% below average)
    elif diff > 0.15: return 2 # Overpriced (15% above average)
    else: return 1             # Fair Price

# 3. Create the new target
y_class_train = np.array([label_deal(a, p) for a, p in zip(actual_prices, predicted_prices)])
y_class_test = np.array([label_deal(a, p) for a, p in zip(y_test, dnn_preds)])

# Convert to one-hot encoding for the Neural Network
y_class_train_cat = to_categorical(y_class_train, num_classes=3)
y_class_test_cat = to_categorical(y_class_test, num_classes=3)
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
```

2. DNN Classifier Architecture

This model predicts the category directly.

```python
from tensorflow.keras import layers, models

classifier_model = models.Sequential([
    layers.Input(shape=(X_train_ready.shape[1],)),
    layers.Dense(64, activation='relu'),
    layers.Dense(32, activation='relu'),
    layers.Dense(3, activation='softmax') # 3 units for 3 classes
])

classifier_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train
classifier_model.fit(X_train_ready, y_class_train_cat, epochs=50, batch_size=32, verbose=0)
print("✅ Deal Classifier Trained.")
```

```
✅ Deal Classifier Trained.
```

4B: Autoencoder Similarity Engine ("You Might Also Like")

Unlike the classifier, an Autoencoder ignores labels like "Price." It learns to compress all the car's features into a tiny "Latent Vector" (an embedding). If two cars have similar embeddings, they are structurally similar (same brand, similar mileage, similar condition).

1. Build and Train the Autoencoder

```python
input_dim = X_train_ready.shape[1]
latent_dim = 8  # We compress the car features into just 8 numbers

# Encoder
input_layer = layers.Input(shape=(input_dim,))
encoded = layers.Dense(32, activation='relu')(input_layer)
latent_space = layers.Dense(latent_dim, activation='relu', name='latent_layer')(encoded)

# Decoder
decoded = layers.Dense(32, activation='relu')(latent_space)
output_layer = layers.Dense(input_dim, activation='sigmoid')(decoded)

# Full Autoencoder
autoencoder = models.Model(input_layer, output_layer)
autoencoder.compile(optimizer='adam', loss='mse')

# Train it to reconstruct itself
autoencoder.fit(X_train_ready, X_train_ready, epochs=100, batch_size=32, verbose=0)

# Extract only the Encoder part for our similarity engine
encoder_only = models.Model(input_layer, latent_space)
```

2. Creating the "Similar Cars" Search Now, we can find cars that are "mathematically closest" to a target car.

```
from sklearn.metrics.pairwise import cosine_similarity

# 1. Generate embeddings for all cars in the dataset
car_embeddings = encoder_only.predict(X_train_ready)

def get_recommendations(car_index, top_k=5):
    # Get the embedding for our target car
    target_embedding = car_embeddings[car_index].reshape(1, -1)

    # Calculate similarity with all other cars
    similarities = cosine_similarity(target_embedding, car_embeddings).flatten()

    # Get indices of the most similar cars (excluding the car itself)
    similar_indices = similarities.argsort()[-(top_k+1):-1][::-1]

    return similar_indices

# Example: Get recommendations for the first car in the training set
rec_indices = get_recommendations(0)
print(f"If you like car #0, you might also like these indices: {rec_indices}")
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
If you like car #0, you might also like these indices: [ 327 1171  435  773 1066]
```

The Master Inference Function

```
def analyze_car_listing(car_details, original_df, preprocessor, reg_model, class_model, encoder, embeddings):
    """
    Comprehensive analysis of a car listing: Price Prediction, Deal Classification,
    and Similarity Recommendations.
    """
    # Prepare the input data
    input_df = pd.DataFrame([car_details])

    # Apply the same Feature Engineering from Phase 1
    input_df['Car_Age'] = 2025 - input_df['Year']
    processed_input = preprocessor.transform(input_df.drop(columns=['Year']))

    # Price Prediction (DNN Regression)
    # Provides the state-of-the-art price estimate
    predicted_price = reg_model.predict(processed_input).flatten()[0]

    # Deal Classification (DNN Classifier)
    # Highlights the best deals on the market
    class_probs = class_model.predict(processed_input)
    class_idx = np.argmax(class_probs)
    deal_labels = {0: "Good Deal", 1: "Fair Price", 2: "Overpriced"}
    deal_status = deal_labels[class_idx]

    # Similarity Matching (Autoencoder)
    # Recommends similar vehicles based on core attributes
    input_embedding = encoder.predict(processed_input)
    similarities = cosine_similarity(input_embedding, embeddings).flatten()
    top_indices = similarities.argsort()[-4:-1][::-1] # Top 3 similar cars
```

```
    similar_cars = original_df.iloc[top_indices]

    # --- Output Report ---
    print(f"--- Market Analysis for {car_details['Brand']} {car_details['Model']} ---")
    print(f"Estimated Market Price: ${predicted_price:,.2f}")
    print(f"Deal Assessment: {deal_status}")
    print("\nSimilar vehicles you might also like:")
    display(similar_cars[['Brand', 'Model', 'Year', 'Mileage', 'Price']])

# Example Usage
new_car = {
    'Brand': 'Toyota',
    'Model': 'Camry',
    'Year': 2018,
    'Engine Size': 2.5,
    'Fuel Type': 'Petrol',
    'Transmission': 'Automatic',
    'Mileage': 45000,
    'Condition': 'Excellent'
}

analyze_car_listing(new_car, df, preprocessor, dnn_model, classifier_model, encoder_only, car_embeddings)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 317ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 246ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 225ms/step
--- Market Analysis for Toyota Camry ---
Estimated Market Price: $40,021.61
Deal Assessment: Good Deal

Similar vehicles you might also like:
```

	Brand	Model	Year	Mileage	Price
723	Toyota	Corolla	2001	229728	35593.06
1457	Ford	Fiesta	2001	214020	90105.17
1626	Toyota	RAV4	2000	120623	98493.27

Visualizing the Autoencoder's "Brain" with t-SNE

t-SNE (t-Distributed Stochastic Neighbor Embedding) takes the 8-dimensional vectors created by our encoder and squashes them into a 2D map. If the Autoencoder worked, cars that are similar will appear as clusters on this map.

```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import seaborn as sns

# 1. Generate embeddings for all training data
# These are the 8-dimensional 'latent vectors' mentioned in your plan
embeddings = encoder_only.predict(X_train_ready)

# 2. Reduce dimensions from 8 to 2 using t-SNE
tsne = TSNE(n_components=2, perplexity=30, random_state=42)
embeddings_2d = tsne.fit_transform(embeddings)
```

```
# 3. Create a plotting dataframe
vis_df = pd.DataFrame(embeddings_2d, columns=['x', 'y'])
vis_df['Brand'] = X_train['Brand'].values
vis_df['Price'] = y_train.values

# 4. Plot the results
plt.figure(figsize=(12, 8))
scatter = sns.scatterplot(
    data=vis_df,
    x='x', y='y',
    hue='Brand',      # Color by Brand to see if the AI grouped them
    palette='viridis',
    alpha=0.7
)
plt.title("Latent Space Visualization: How the Autoencoder 'Sees' Car Similarity")
plt.legend(bbox_to_anchor=(1.05, 1), loc=2)
plt.show()
```

```
63/63 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
```